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Extending the Front: Designing RFID Antennas using Multiobjective Differential Evolution with Biased Population Selection

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Abstract

RFID antennas are ubiquitous, so exploring the space of high efficiency and low resonant frequency antennas is an important multiobjective problem. Previous work has shown that the continuous solver differential evolution (DE) can be successfully applied to this discrete problem, but has difficulty exploring the region of solutions with lowest resonant frequency. This paper introduces a modified DE algorithm that uses biased selection from an archive of solutions to direct the search toward this region. Results indicate that the proposed approach produces superior attainment surfaces to the earlier work. The biased selection procedure is applicable to other population-based approaches for this problem.

Keywords: multiobjective optimisation, weighted preferences, RFID antenna design, differential evolution

1 Introduction

First introduced in 1948 [21], radio frequency identification (RFID) has become one of the major methods for the tracking and identification of goods and items, particularly within logistics and supply chains [9]. An RFID system consists of two basic components: a reader and a tag (containing an antenna). The reader sends an RF signal which can power the receiver (the tag). This in turn will radiate back a signal to the reader [20]. This backscattered signal usually contains a number that uniquely identifies the tag, and hence item. A key design objective for the antenna is improving the read range (the distance the signal can be sent and received), which is affected by two main factors: read range is generally inversely proportional to an antenna's *resonant frequency*, f_0 , and proportional to its gain (related to its *efficiency*,

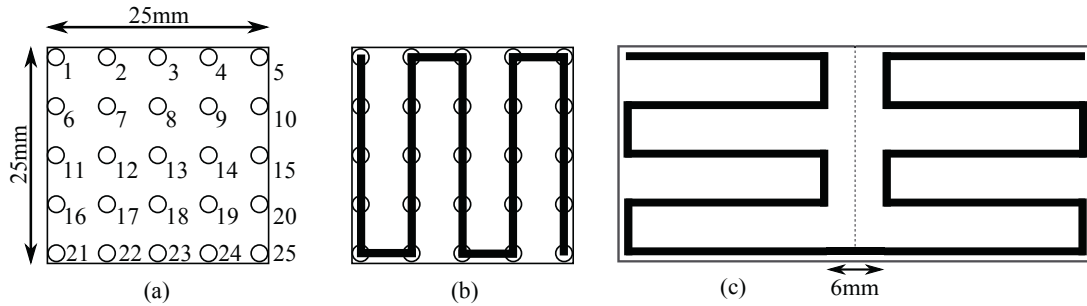


Figure 1: (a) A 5×5 antenna grid. (b) A meander line RFID antenna defined on that grid. (c) The complete dipole antenna produced by mirroring the solution shown in (b); the two halves are joined by a 6mm bridge.

η). Both these factors are determined by the design of the antenna, and hence become a multiobjective optimisation (MOO) problem.¹ It is desirable to minimise f_0 and maximise η . This is achieved by producing antennas that maximise the length of the antenna in a convoluted space-filling manner. RFID antennas are usually designed in such a way that they form meander lines as dipole structures. An example of such an antenna is given in Figure 1. Note that these antennas can be laid out on a Cartesian grid and are symmetrical around the dipole, so only one half of the antenna needs to be designed by an algorithm. The number of points in the grid defines the problem. Previous work examined grids between five and 10 nodes, as does this paper.

1.1 Designing and Optimising RFID Antennas

Meander line RFID antennas have traditionally been designed manually either using engineers' understanding of the interactions between antenna segments, or based on simple designs such as a plough (see Figure 1) or spiral. These antenna designs have all been of the maximum length possible. Gelehdar, Thiele and O'Keefe [7] were the first to explore the search space of the problem, enumerating solutions on a 5×5 grid (a very small size). Since 2007 metaheuristics have been applied to explore the space of meander line antennas and provide a range of alternative trade-off designs (see, e.g., [8, 11, 12, 16, 19, 22]). In addition to demonstrating that such automated design is possible, these studies showed that antennas may be shorter than the maximum length while still achieving high efficiency and low resonant frequency, which in turn makes the search space easier to navigate.

Producing a meander line antenna is essentially a constructive activity, so the first optimisation heuristic to be applied was the constructive metaheuristic ant colony optimisation (ACO), initially to single-objective formulations [19, 22] and then to the multiobjective problem described here [12, 11]. To provide comparative results using a very different approach, in 2011 Montgomery, Randall and Lewis [16] presented an adaptation of the continuous differential evolution [18] metaheuristic to the problem, which encoded constructive moves into each dimension of a real-valued space. An updated version of that algorithm is used in the current work and described in more detail in Section 2 below. More recently, extremal optimisation

¹This paper assumes some degree of familiarity with MOO. See Coello Coello [3] or Deb [4] for good introductions to the topic.

has also been applied to the problem [8].

Although posed as a MOO problem, not all regions of the Pareto front are of equivalent interest, with solutions of lower resonant frequency (yet highest efficiency possible) preferred. Most previous applications of heuristic solvers to this problem aimed to achieve good approximations of the (unknown) Pareto front without incorporating this preference. In order to encourage exploration of (near-)Pareto optimal solutions with lower resonant frequency, the earlier DE work [16] tested a minimum length constraint, which considered any antenna less than half the maximum length as infeasible, and hence dominated by any longer solution. The constraint was placed on antenna length, rather than on objective value, because very short antennas have a tendency to be highly efficient. As that version of the algorithm used a single population of 100 individuals to both generate new solutions and represent the archive of best solutions, these short antennas, once generated, might never be replaced as they were non-dominated in the efficiency objective. The use of the minimum length constraint was successful in increasing the proportion of solutions with low resonant frequency for grid sizes up to eight, but retarded the search in larger grid sizes.

This paper investigates an alternative mechanism to direct the search: biased selection of the working population from a larger archive of non-dominated solutions (sometimes referred to as ‘weighted preferences’ in the literature). As this is the focus of this work, no comparisons will be made between the current DE algorithm and the prior version, nor with the ACO or EO algorithms. A detailed comparison of the design choices made in the new DE algorithm, including inter-algorithm comparisons, will be presented in a forthcoming work [17].

The next section describes the DE algorithm and its application to RFID antenna design, while Section 3 describes the bias mechanism that will be used. The approach is evaluated in Section 4.

2 Differential Evolution for RFID Antenna Design

DE is a population-based search heuristic that operates in continuous domains and which has been applied successfully to many different problems [18]. Single-objective DE algorithms operate a generational model where, at each iteration, each solution is considered as a *target* for replacement by a newly generated solution. Adaptations of DE to MOO vary in their similarity to DE for single-objective optimisation [13]. The heuristic solver used in this work is a multiobjective DE/rand/1/exp algorithm that uses Pareto ranking to select between archived and newly generated solutions. This means that it retains the solution mutation mechanism of DE but uses general-purpose MOO mechanisms to manage the population and archive of known good solutions, in this case the non-dominated sorting component of Deb *et al.*’s NSGA-II [5].

The DE/rand/1/exp algorithm variant was selected previously [16] as the DE/rand/1/* family of algorithms is both widely-used and effective [14]. The *exp* crossover, which takes contiguous components from an intermediate candidate solution during crossover, is used as prior testing [16] found it to be more effective on this problem than DE/rand/1/bin.

2.1 Population Archive

While the previous DE algorithm maintained a single working population that also served as the archive, the present algorithm maintains an independent archive that can, when all solutions within it are non-dominated, grow larger than the population. For each iteration, a new working population is drawn from the archive (Section 3 describes how this may be biased). Then, for each member of the population, a new solution is generated using that population member as

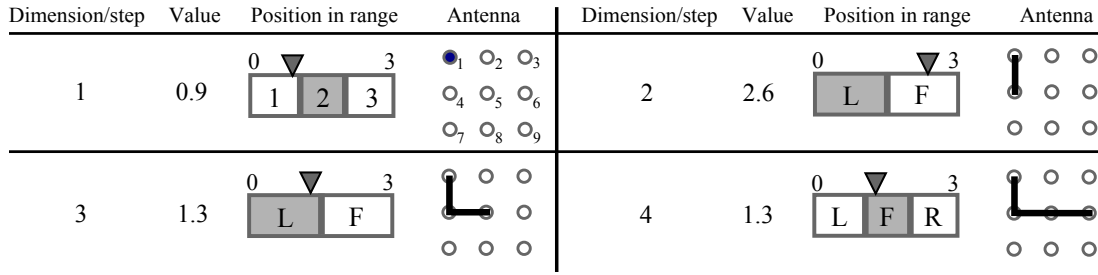


Figure 2: Decoding a vector in continuous space to construct an RFID antenna. The shaded portion of each range indicates the starting node or direction chosen. The range of each dimension $[0, 3]$ is independent of the grid size.

one of the three ‘parents’ (its role in mutation is the same as *target* although it will actually compete with all children generated during that iteration). The newly generated solutions are combined with the archive and non-dominated sorting is performed to eliminate the poorest solutions.

2.2 Mapping Antenna Designs to Continuous Space

Antennas are encoded as a series of construction decisions, beginning with the selection of an initial node along the ‘top’ edge of the grid, followed by a set of moves expressed in relative directions. This representation, and the use of relative rather than absolute directions, was selected because it has previously been found to be more effective in evolutionary algorithms (EAs) for the related problem of constructing self-avoiding walks [1]. The ability to select a starting node was not present in the previous DE algorithm, which started all antennas from node 1 [16]. This provides access to the complete search space of meander line antennas; the impact of this change will be examined in a forthcoming work. Construction is assumed to be pointing ‘down’ from this starting node, and proceeds by moving along edges either *(L)eft*, *(F)orward* or *(R)ight* from successive nodes, until no further edges can be constructed.² The maximum number of such instructions on an $m \times m$ grid is $m^2 - 1$. Thus, including the selection of an initial node, each DE solution is a vector in $n = m^2$ dimensional space, where the first dimension describes the starting node, the second dimension the relative direction to move from that node, and so on. Each dimension is over the (arbitrary) range $[0, 3]$, and is divided into three areas corresponding to *L*, *F* and *R*, respectively.

To encourage the construction of longer antennas, the interpretation of a component’s value is altered adaptively such that only currently feasible directions are represented. For example, if only the directions *L* and *F* are possible from a given node, the corresponding dimension’s range is considered to be divided in two, the lower half representing the direction *L* and the upper half the direction *F*. Consequently, a value in $[0, 1)$ represents a *tendency* to go left at that point, a value in $[1, 2)$ a tendency to go forward, etc. In this way the solution representation in continuous space has an intuitive correspondence with its discrete counterpart. Figure 2 illustrates this solution encoding and how it is interpreted during antenna construction.

²The previous work referred to the forward direction as (S)traight.

3 Directing the Search via Biased Archive Selection

Zitzler, Brockhoff and Thiele [23] propose a number of weighting (i.e., bias) functions to incorporate user preference information into multiobjective optimisation with hypervolume-based EAs. In the following, assume that each objective value x_i has been normalised to lie in the range $[0,1]$, where a value of 1 corresponds to the current observed best value for that objective while 0 corresponds to the current observed worst value. Zitzler *et al.* introduce a number of weighting functions for bi-objective problems, including w^{ext} , which represents a bias towards the best solutions in any objective, and w^{asym} , which represents a bias towards a single objective:

$$w^{ext}(x) = \frac{\sum_{i=1}^m e^{20 \cdot x_i}}{m \cdot e^{20}}$$

$$w^{asym}(x) = e^{20 \cdot x_1} / e^{20}$$

Friedrich, Kroeger and Neumann [6] later showed how Zitzler *et al.*'s weighting functions can be incorporated into other algorithms that are not based on hypervolume, such as NSGA-II. A key feature NSGA-II is its use of a diversity mechanism based on a measure of how crowded each solution is within its front, i.e., how near it is to its neighbours in objective space. This is applied to the last front and can be used to eliminate crowded solutions to maintain a fixed archive size. (In the present work, crowding is used for this purpose until only a single front exists in the archive, at which point it may grow indefinitely.) In NSGA-II, a solution's *crowding distance* is the sum of the relative distance between its two adjacent solutions in each objective. Solutions at the extreme of each objective are assigned a crowding distance of ∞ . Friedrich *et al.* combine a solution's crowding distance with its bias weight.

The approach used here is an adaptation of w^{ext} that allows any number of objectives to be weighted by varying degrees:

$$w^{var} = \frac{\sum_{i=1}^m e^{20 \cdot b_i \cdot x_i}}{\sum_{i=1}^m e^{20 \cdot b_i}} \quad (1)$$

where b is a vector of bias weights, which sum to 1. When all weights in b are equal, Equation 1 leads to equivalent bias behaviour as w^{ext} , while when one weight is 1 (and the others 0) it is equivalent to w^{asym} .

In the present algorithm, when the archive is larger than the working population and no bias is being used, solutions are drawn from the archive with uniform probability. When the bias is in effect, solutions are drawn in non-increasing order of their crowding distance, which incorporates the bias weighting.

4 Computational Experience

Experiments concerned grid sizes between 5×5 and 10×10 with a fixed track width of 1mm and grid dimensions of 25×25 mm, as used in both the previous study and Lewis *et al.* [12]. Experiments were conducted on a virtual Linux machine with four processing cores. Solutions were evaluated using a modified version of NEC [2], based on source code from late October 2010 (the same version used in [16]). As the largest antennas can take more than 160 seconds to be evaluated, a solution cache is employed so that rediscovered solutions are not re-evaluated. Four solutions are evaluated simultaneously (one per core), so any runtimes mentioned below

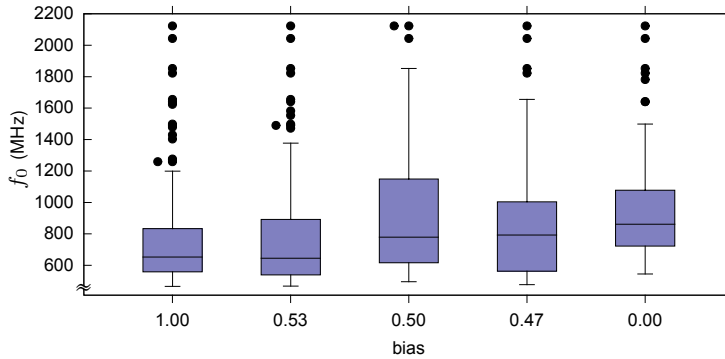


Figure 3: Distributions over f_0 for 7×7 problem with different biases towards f_0

represent approximately one quarter of the total computing time required. Solution evaluation thus dominates computation time, with runs on the largest grid size of 10×10 taking approximately one day wall clock time, with the DE algorithm (and any bias mechanism employed) occupying only a few minutes of this time.

Prior work [16] found that a DE/rand/1/exp algorithm with crossover $Cr = 0.99$ and vector scale factor $F = 0.8$ worked well with this problem model, so the same configuration is used here. The algorithm’s working population (and archive) begin with 50 randomly initialised solutions. This is half the size used in the previous work, where the population also served as archive, as an external archive is now available and smaller populations have been shown to work well with DE [15]. Each run was allowed to produce 10,000 solutions (200 iterations) in addition to the 50 in the initial population. Three variants of the algorithm are examined in the following sections: DE with no bias; DE with the minimum length constraint introduced by Montgomery *et al.* [16], referred to as DE_{minL} ; and DE with the weighted bias described above, referred to as DE_{bias} .

4.1 Varying the Bias between Extremes

An initial study was conducted into the efficacy of the variable weighting mechanism introduced in Section 3. Bias favouring resonant frequency f_0 was varied across five runs on a 7×7 grid with values of $b = 1, 0.53, 0.5, 0.47$ and 0 (the bias values for η are the complement of each). Each bias setting is referred to hereafter as b^{bias} , as in $b^{0.47}$. The values 0.53 and its complement were chosen by inspecting the bias function’s landscape to select values likely to produce behaviour intermediate between the extremes and 0.5. The grid size 7×7 is large enough for differences to be apparent while having a relatively low runtime (approximately nine hours per run).

Figure 3 shows box plots of the distributions of f_0 , the objective of most interest, for each bias setting. A trend from low to high values of f_0 is apparent. As the data are non-normally distributed a Kruskal-Wallis test was performed across the five distributions, which showed a statistically significant difference existed. Pairwise Mann-Whitney U tests confirmed that most of the differences between pairs of distributions are statistically significant at the 1% level, except between b^1 and $b^{0.53}$ and between $b^{0.5}$ and both $b^{0.47}$ and b^0 .

Biassing the search towards f_0 also increases the size of the final solution set, with the runs b^1 through b^0 producing final solution sets of 213, 186, 126, 135 and 131 solutions, respectively. Hypervolume values (not reported but available upon request) also show a trend to better

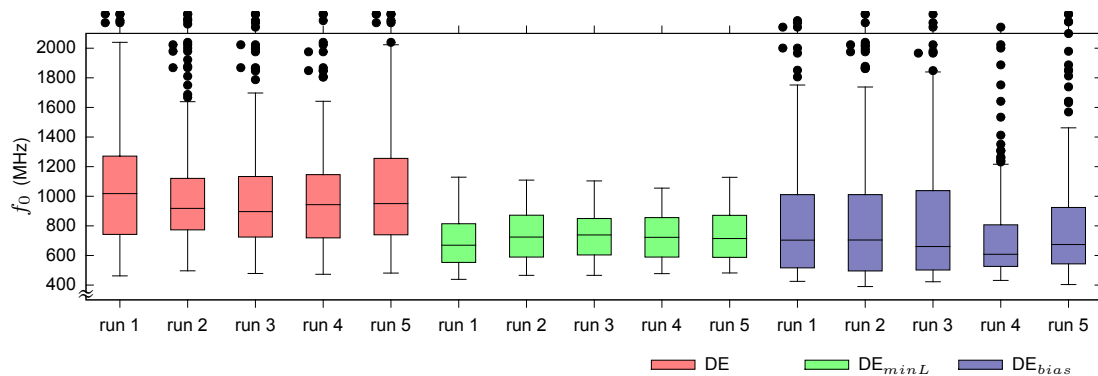


Figure 4: Distributions over f_0 for each run on 10×10 problem

attainment surfaces as the bias is increased to 1. Although this study is small, with only a single sample (i.e., distribution) per bias setting, the differences observed and the apparent trend in attainment surface size indicate that bias b^1 (equivalent to the w^{asym} weighting function) is suitable for directing the search to antennas with low f_0 , so this setting is used by DE_{bias} in subsequent experiments.

4.2 Biasing the Search toward Lower Resonant Frequency

In the following experiments DE, DE_{minL} and DE_{bias} (with bias b^1) were run across five random seeds on each grid size from 5×5 to 10×10 . Figure 4 shows the distributions over f_0 achieved in each run of the three algorithms on the 10×10 grid. DE_{bias} is clearly superior to DE in producing antennas with low f_0 . The distributions for DE_{minL} indeed focus on lower f_0 solutions, since by excluding antennas below half length it also excludes solutions with f_0 greater than approximately 1100MHz. However, its performance is still not as good as DE_{bias} when various metrics are considered.

Table 1 presents summary metrics across the three algorithms: hypervolume,³ minimum f_0 present in the solution set, total size of the solution set and number of solutions with $f_0 \leq 600$ MHz. The best value within each problem size–statistic group is bolded. It is evident that DE_{bias} not only produces a greater number of solutions but also a greater number of solutions in the area of most interest and, typically, the best solutions in terms of f_0 .

To visualise the distribution of solutions across both objectives, Figure 5 shows the best, median and worst summary attainment surfaces, calculated according to Knowles’ [10] approach, for grid sizes 8×8 to 10×10 . Note these are not the actual solution sets produced but the boundaries within which the best, median or worst solution sets may be found. These confirm that DE_{minL} can improve on the performance of DE in terms of the area dominated by the solution sets it produces, especially in the number of low resonant frequency solutions produced. However, as was found earlier [16], it appears to reduce the algorithm’s ability to ‘fill in’ the front, especially on the largest grid size. Overall, the use of biased archive selection produces

³Hypervolumes were calculated by subtracting f_0 values from 2,250 (to transform f_0 into a maximisation objective) and multiplying η values by 20 so that both objectives were of similar magnitude. The reported values have been normalised by the maximum possible—but not practically achievable—area determined by these upper bounds, then multiplied by 100 for readability. The original solution sets are available upon request.

Table 1: Best, median and worst results for hypervolume, minimum f_0 , solution set size and number of solutions with $f_0 \leq 600$ MHz.

		Hypervolume			Minium f_0			total solutions...			...with $f_0 \leq 600$		
		best	med	worst	best	med	worst	best	med	worst	best	med	worst
5×5	DE	73.8	73.8	73.8	574	574	574	104	103	102	9	9	9
	DE _{minL}	73.7	73.7	73.7	574	574	574	101	95	92	9	9	9
	DE _{bias}	73.8	73.8	73.8	574	574	574	100	97	97	10	9	9
6×6	DE	76.2	75.5	75.4	514	533	536	154	143	140	42	24	12
	DE _{minL}	76.1	76.1	75.9	514	516	520	154	143	124	44	31	26
	DE _{bias}	76.3	76.2	76.2	514	514	514	188	168	148	67	61	30
7×7	DE	77.8	77.0	76.0	472	495	518	195	179	134	48	28	17
	DE _{minL}	77.9	76.4	75.3	466	504	529	172	145	130	58	46	11
	DE _{bias}	78.2	78.2	77.6	464	464	478	217	197	164	113	87	41
8×8	DE	78.4	77.7	76.8	457	476	497	205	183	146	42	33	25
	DE _{minL}	77.7	77.4	76.7	468	473	493	190	156	119	63	28	19
	DE _{bias}	79.5	79.2	77.0	427	436	492	267	252	191	167	129	79
9×9	DE	78.6	77.6	77.0	451	476	488	208	187	172	40	33	23
	DE _{minL}	79.3	77.4	76.7	423	471	489	169	146	108	67	30	23
	DE _{bias}	80.3	79.8	79.4	404	418	431	295	270	222	138	131	99
10×10	DE	77.9	77.4	76.6	462	479	496	199	190	181	27	24	19
	DE _{minL}	78.3	77.0	76.8	439	466	482	144	128	106	39	35	30
	DE _{bias}	80.8	79.4	79.2	390	422	431	266	229	204	113	98	80

the best results in terms of number of solutions, quality of the front (and its likely proximity to the true Pareto front), and ability to focus on antenna designs with low resonant frequency.

5 Concluding remarks

In the objective space of low resonant frequency and high efficiency RFID antennas, the region of most interest is that containing solutions with lowest resonant frequency. Previous work applied DE to this problem used a minimum antenna length constraint to encourage exploration of this region, but this was only partially successful. The present work used biased selection from the solution archive instead, and was successful in producing high quality attainment surfaces that both extend the solution set's reach along the f_0 objective and produce good coverage along the entire front. The mechanism employed is easily transferable to other population-based techniques for this problem if they use (or can use) separate archive and working populations.

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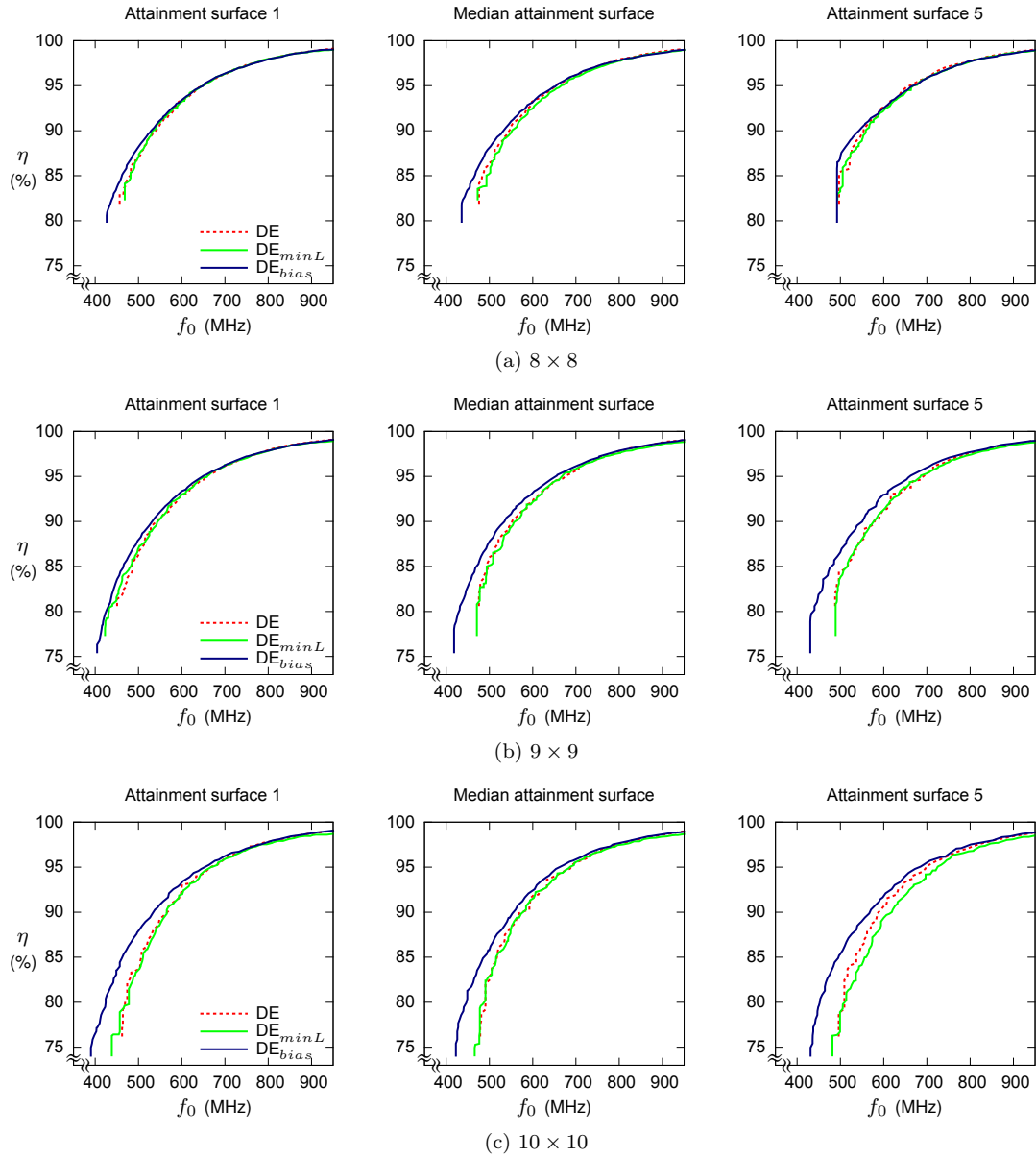


Figure 5: First (best), median and last attainment surfaces

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